THE MULTIDIMENSIONAL IMPACT OF ARTIFICIAL INTELLIGENCE ADOPTION ON DIGITAL TRANSFORMATION IN SMALL AND MEDIUM-SIZED ENTERPRISES IN VIETNAM

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Abstract: ***This study examines the multidimensional impact of artificial intelligence (AI) adoption on the digital transformation of small and medium-sized enterprises (SMEs) in Vietnam. Drawing on the Resource-Based View (RBV), Dynamic Capability Theory, and the Technology-Organization-Environment (TOE) framework, the study proposes a model that conceptualizes AI adoption across three dimensions: Operational AI, Analytical AI, and Customer-Facing AI, while treating digital transformation as a single composite construct reflecting the overall level of organizational digitalization. Using PLS-SEM with survey data from 200 Vietnamese SMEs, the results confirm that all three AI dimensions exert significant positive effects on digital transformation. Operational AI demonstrates the strongest impact (β = 0.38), followed by Analytical AI (β = 0.27) and Customer-Facing AI (β = 0.19). Firm size positively moderates the relationship between Analytical AI and digital transformation, while industry sector moderates the effect of Customer-Facing AI. The findings provide valuable empirical evidence on the differentiated pathways through which AI drives digital transformation in an emerging economy context, with practical implications for SME managers and policymakers.***

• Keywords: *artificial intelligence, digital transformation, small and medium-sized enterprises, operational AI, analytical AI, customer-facing AI, PLS-SEM, Vietnam.*

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1. Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technologies of the digital era, reshaping how firms operate, compete, and create value (Brynjolfsson & Mcafee, 2017). However, AI is not a monolithic technology, different forms of AI application, such as operational AI, analytical AI, and customer-facing AI, may influence digital transformation through distinct mechanisms and to varying degrees. Understanding these differences carries important theoretical and practical implications, particularly for small and medium-sized enterprises (SMEs) whose constrained resources necessitate careful prioritization of AI investment to maximize digital transformation outcomes.

In Vietnam, SMEs account for more than 97% of all active enterprises and contribute approximately 45% of national GDP; yet their pace of digital transformation remains relatively slow compared to large enterprises and to regional peers. According to the Ministry of Information and Communications, only around 20% of Vietnamese SMEs have deployed at least one AI-enabled solution, compared to rates exceeding 50% in Singapore and South Korea. This gap raises a critical question: which AI adoption pathway delivers the greatest digital transformation impact given the resource constraints and limited digital infrastructure characteristic of Vietnamese SMEs?

Although the relationship between AI adoption and digital transformation has been addressed in recent literature (Mikalef, Conboy, & Krogstie, 2021), most studies treat AI adoption as a unidimensional construct, stopping short of disaggregating and comparing the effects of distinct AI forms on digital transformation outcomes. This constitutes the theoretical and empirical gap the present study seeks to address.

Specifically, the paper pursues three research questions: (1) How do the three dimensions of AI adoption (Operational AI, Analytical AI, and Customer-Facing AI) affect digital transformation in SMEs? (2) Which AI dimension exerts the strongest overall effect? (3) How do contextual factors such as firm size and industry sector moderate these relationships?

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The paper makes three contributions. Theoretically, it proposes and empirically tests a multidimensional AI-impact model treating the three AI dimensions as distinct predictors of a single digital transformation construct enabling direct comparisons of their relative effects. Empirically, it provides quantitative evidence from an emerging economy with a sample of 200 SMEs. Practically, the findings equip Vietnamese SME managers with evidence-based guidance on which AI investment to prioritize given their specific resource context.

2. Theoretical Background and Hypothesis Development

2.1. Theoretical Foundations

(1) Resource-Based View (RBV)

The Resource-Based View (Barney, 1991) posits that sustainable competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable (VRIN criteria). In the digital economy, AI can serve as a strategic technological resource capable of satisfying these criteria when embedded in firm-specific operational processes. More importantly, from the Resource-Based View (RBV), it can be inferred that different forms of AI applications will influence different organizational capabilities: Operational AI improves process efficiency, Analytical AI strengthens data capabilities, and Customer-Facing AI expands market-facing capabilities, thereby generating differential contributions to overall digital transformation.

(2) Dynamic Capability Theory

Dynamic Capability Theory (Teece, Pisano, & Shuen, 1997) emphasizes a firm's capacity to sense opportunities, seize resources, and reconfigure organizational assets in volatile environments. Within this framework, each AI dimension activates a distinct reconfiguration mechanism: Operational AI drives process reconfiguration, Analytical AI drives data capability reconfiguration, and Customer-Facing AI drives customer-centric business model reconfiguration. Each mechanism contributes to overall digital transformation through a different pathway, yet all ultimately converge on the common outcome of higher organizational digitalization.

Technology-Organization-Environment (TOE) Framework

The TOE framework (Tornatzky, Fleischer, & Chakrabarti, 1990) explains that technology adoption outcomes are shaped jointly by technological, organizational, and environmental factors. In the present research context, TOE provides the theoretical rationale for why firm size and industry sector moderate the AI-digital transformation relationship: larger firms possess greater resources to leverage Analytical AI, while service-sector firms operate in environments more conducive to exploiting Customer-Facing AI. Both contextual factors may amplify or constrain the digital transformation impact of each AI dimension.

2.2. Construct Definitions and Measurement

AI adoption is defined as the degree to which a firm deploys and integrates AI technologies into its business operations to automate processes, analyze data, and enhance customer interactions (Wamba-Taguimdje et al., 2020). The study operationalizes AI adoption across three dimensions.

The first dimension, Operational AI, captures the extent to which a firm uses AI to automate operational processes, optimize supply chains, and improve production efficiency. This form of AI is the most prevalent among SMEs owing to its relatively lower deployment cost and comparatively clear short-term impact on operational performance.

The second dimension, Analytical AI, reflects the extent to which a firm uses AI for data analysis, market trend forecasting, and business decision support. Analytical AI demands a sufficiently large data foundation and robust digital infrastructure, making it more common among larger SMEs.

The third dimension, Customer-Facing AI, captures the extent to which a firm deploys AI at customer touchpoints - including chatbots, personalized recommendation systems, and customer behavior analytics. This form of AI is growing rapidly among SMEs in the commerce and service sectors.

Digital transformation is defined as the degree to which a firm integrates digital technologies across its entire operations, resulting in fundamental changes in how value is created and delivered to customers (Vial, 2019). Following Matt et al. (2015), who argue that digital transformation is a holistic organizational transition that cannot be cleanly partitioned into independent sub-dimensions, this study treats digital transformation as a single composite construct reflecting the firm's overall level of digitalization. This approach is particularly appropriate for SMEs, where the boundaries between process digitalization, data integration, and business model innovation are rarely distinct.

2.3. Hypothesis Development

Building on the three theoretical foundations above, the study develops five hypotheses concerning

the effects of each AI dimension on digital transformation and the moderating role of contextual factors. H1: Operational AI has a positive effect on digital transformation in SMEs; H2: Analytical AI has a positive effect on digital transformation in SMEs; H3: Customer-Facing AI has a positive effect on digital transformation in SMEs; H4: Firm size positively moderates the relationship between Analytical AI and digital transformation; H5: Industry sector moderates the relationship between Customer-Facing AI and digital transformation.

3. Research Methodology

3.1. Research Design and Data Collection

The study adopts a quantitative cross-sectional survey design. Primary data were collected via a structured questionnaire administered to owners, chief executives, and senior managers of Vietnamese SMEs. Eligibility criteria required firms to: (1) qualify as SMEs under Decree 80/2021/ND-CP, (2) have deployed at least one AI or digital technology solution, and (3) have been in operation for a minimum of two years.

Sample size was determined following the PLS-SEM "10-times rule", which requires a minimum sample of ten times the largest number of indicators associated with any single latent variable or the maximum number of paths directed at any endogenous construct (Hair et al., 2022). With the AI adoption construct comprising 12 indicators, the minimum required sample was 120 observations. To ensure adequate statistical power and generalizability, a final valid sample of 200 observations was targeted and achieved.

3.2. Measures

All variables were measured using five-point Likert scales (1 = strongly disagree to 5 = strongly agree). The AI adoption scale comprises 12 items reflecting the three dimensions: Operational AI items capture process automation and internal decision support; Analytical AI items reflect the firm's capacity to extract insights from data for managerial purposes; and Customer-Facing AI items assess the degree to which AI personalizes service delivery and enhances customer experience. Items were adapted from Wamba-Taguimdje et al. (2020) and Mikalef & Gupta (2025).

The digital transformation scale comprises 6 items measuring the firm's overall digitalization level. The items collectively reflect three complementary aspects: (i) process digitalization (extent of digitizing production, business, and internal management activities), (ii) data integration and exploitation (ability to link, share, and use data in decision-making), and (iii) business model innovation (using digital technology to create new value, distribution channels, or customer service modalities). This approach draws on Vial (2019) and Matt et al. (2015), treating digital transformation as a unitary latent construct indicative of the firm's digital maturity.

Moderating variables include firm size, measured by number of employees and annual revenue in line with prior research on SME performance and digital transformation, and industry sector, classified into three groups: manufacturing, commerce, and services, to capture differences in technological characteristics and digital transformation propensity across industries.

3.3. Analytical Approach

Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted using SmartPLS 4.0. The analysis followed a two-step procedure. Step 1 evaluated the measurement model by examining reliability (Cronbach's Alpha and composite reliability, CR), convergent validity (average variance extracted, AVE), and discriminant validity (Heterotrait-Monotrait ratio, HTMT). Step 2 evaluated the structural model through path coefficients, the coefficient of determination R^2, and bootstrapped significance tests using 5,000 subsamples. The moderating effects of firm size and industry sector were tested via PLS-SEM interaction analysis.

4. Results

4.1. Sample Characteristics

The final sample comprised 200 Vietnamese SMEs with diverse profiles. By firm size, micro-enterprises (fewer than 10 employees) accounted for 27.5%, small enterprises (10-50 employees) for 46.5%, and medium enterprises (51-200 employees) for 26.0%. By industry sector, manufacturing represented 31.0%, commerce 39.5%, and services 29.5%. Most firms had been in operation for five or more years (68.5%). Respondents were predominantly business owners or CEOs (72.0%), with the remainder being managers responsible for digital transformation.

In terms of AI adoption levels, Customer-Facing AI was the most widely deployed (66.5% of firms reported at least some adoption), followed by Operational AI (59.0%) and Analytical AI (47.5%). This pattern reflects a tendency among Vietnamese SMEs to prioritize consumer-facing and

process-automation AI before investing in the data infrastructure required for analytical applications.

Table 1. Sample Characteristics (N = 200)

Characteristic	Frequency (n)	Percentage (%)
Firm Size		
Micro (< 10 employees)	55	27.5
Small (10-50 employees)	93	46.5
Medium (51-200 employees)	52	26.0
Industry Sector		
Manufacturing	62	31.0
Commerce	79	39.5
Services	59	29.5
Years in Operation		
Fewer than 5 years	63	31.5
5 years or more	137	68.5

4.2. Measurement Model Evaluation

Prior to hypothesis testing, the measurement model was assessed for reliability and validity following established PLS-SEM criteria (Hair et al., 2017). Results are reported in Table 2.

All Cronbach's Alpha values exceeded the 0.70 threshold, ranging from 0.81 to 0.86. Composite reliability (CR) values were all above 0.85, confirming strong internal consistency. Average variance extracted (AVE) ranged from 0.52 to 0.63, surpassing the 0.50 threshold and confirming convergent validity. All indicator loadings exceeded 0.60 and were statistically significant at $p < 0.001$.

Discriminant validity was assessed using the HTMT criterion. All HTMT values among the three AI dimensions were below 0.85, confirming that the three AI constructs are empirically distinct. Regarding common method bias, Harman's single factor test revealed that a single factor explained only 22.8% of total variance well below the 50% threshold, indicating that common method bias is unlikely to be a serious concern.

Table 2. Measurement Model Results

Construct	Cronbach's α	CR	AVE	Items	HTMT (max)
Operational AI (OAI)	0.84	0.88	0.60	4	0.72
Analytical AI (AAI)	0.81	0.86	0.55	4	0.76
Customer-Facing AI (CFAI)	0.86	0.90	0.63	4	0.68
Digital Transformation (DT)	0.85	0.89	0.52	6	-

4.3. Structural Model and Hypothesis Testing

Following confirmation of measurement model quality, the structural model was evaluated and all five hypotheses were tested via bootstrapping with 5,000 subsamples. Results are presented in Table 3.

The coefficient of determination $R^2 = 0.58$ indicates that the three AI adoption dimensions collectively explain 58% of the variance in digital transformation - a moderate-to-high level of explanatory power in PLS-SEM applications (Hair et al., 2017). Effect sizes (f^2) were 0.24 for Operational AI (medium), 0.14 for Analytical AI (small-to-medium), and 0.09 for Customer-Facing AI (small), consistent with the observed ranking of path coefficients.

Regarding direct effect hypotheses (H1-H3), all three were supported at $p < 0.001$. Operational AI exhibited the largest path coefficient ($\beta = 0.38$, $t = 6.14$), followed by Analytical AI ($\beta = 0.27$, $t = 4.32$) and Customer-Facing AI ($\beta = 0.19$, $t = 3.07$). A bootstrapped difference test confirmed that the gap between H1 and H3 was statistically significant ($p = 0.012$), while the difference between H1 and H2 approached significance ($p = 0.063$).

Regarding moderating hypotheses (H4-H5), both were supported. PLS-SEM interaction analysis revealed that firm size positively and significantly moderated the Analytical AI - digital transformation relationship ($\beta = 0.13$, $t = 2.24$, $p = 0.025$), confirming H4. Specifically, the effect of Analytical AI on digital transformation was substantially stronger for medium-sized enterprises ($\beta = 0.35$) than for micro-enterprises ($\beta = 0.18$). Industry sector similarly moderated the Customer-Facing AI - digital transformation relationship ($\beta = 0.16$, $t = 2.58$, $p = 0.010$), confirming H5. Multi-group analysis (MGA) showed this effect was strongest in the services sector ($\beta = 0.31$), followed by commerce ($\beta = 0.23$) and manufacturing ($\beta = 0.11$).

Table 3. Hypothesis Testing Results (N = 200, Bootstrap = 5,000)

H	Relationship	β	SE	t-value	p-value	Result
H1	Operational AI → Digital Transformation	0.38***	0.062	6.14	0.000	Supported
H2	Analytical AI → Digital Transformation	0.27***	0.063	4.32	0.000	Supported
H3	Customer-Facing AI → Digital Transformation	0.19***	0.062	3.07	0.002	Supported
H4	Firm Size × Analytical AI → DT	0.13**	0.058	2.24	0.025	Supported
H5	Industry × Customer-Facing AI → DT	0.16**	0.062	2.58	0.010	Supported

5. Discussion

5.1. Operational AI as the Primary Digital Transformation Driver

The finding that Operational AI exerts the strongest effect on digital transformation ($\beta = 0.38$, $f^2 = 0.24$) can be explained through two complementary mechanisms. From an RBV perspective, deploying Operational AI compels the entire organizational system to adapt: processes are standardized, digital infrastructure is upgraded, and a data-driven culture begins to take root, generating broad spillover effects on overall digital transformation. From a practical standpoint, Operational AI offers Vietnamese SMEs a higher-return, lower-risk entry point into digital transformation compared to Analytical or Customer-

Facing AI, enabling deeper and more pervasive deployment that accumulates into a larger aggregate effect. These findings are consistent with Dynamic Capability Theory (Teece, Pisano, & Shuen, 1997): the capacity to reconfigure operational processes constitutes the foundational layer on which deeper forms of digital transformation are built.

5.2. Complementary Roles of Analytical AI and Customer-Facing AI

Although Analytical AI (β = 0.27) and Customer-Facing AI (β = 0.19) exhibit weaker individual effects, both dimensions play important and non-substitutable complementary roles in the digital transformation process. Analytical AI generates strategic-level transformation by shifting firms from experience-based to evidence-based decision-making, a hallmark of deep digital transformation. Its impact is, however, constrained by the data infrastructure and analytical workforce requirements that exceed the capacity of many micro and small enterprises, which explains why firm size emerges as a significant moderator (H4 supported). Customer-Facing AI, despite carrying the smallest path coefficient, demonstrates particularly pronounced digital transformation impact in service and commerce sectors where customer experience is the primary competitive differentiator, a pattern captured by the significant moderation of industry sector (H5 supported).

5.3. Managerial Implications

The findings yield four actionable managerial implications for Vietnamese SMEs. First, resource-constrained SMEs should prioritize Operational AI as the strategic first step in their digital transformation roadmap, as it delivers the broadest impact and simultaneously builds the foundation for subsequent AI investments. Second, SMEs that have established robust Operational AI capabilities should expand into Analytical AI to deepen their digital transformation, particularly if they have achieved sufficient scale to exploit data analytics effectively. Third, service and commerce SMEs should treat Customer-Facing AI as a co-priority alongside Operational AI, given that the effect of this AI dimension is significantly amplified in their respective industry environments. Fourth, policymakers designing SME digitalization support programs should adopt context-sensitive approaches differentiated by firm size and industry sector rather than applying uniform frameworks.

Conclusion

This study examined the multidimensional impact of AI adoption on digital transformation among Vietnamese SMEs, with digital transformation operationalized as a single composite construct. Three main contributions are offered. Theoretically, the study proposes and tests a model that disaggregates AI adoption into three distinct dimensions and assesses each dimension's independent effect on a unified digital transformation construct - enabling direct effect-size comparisons that prior unidimensional approaches could not provide. Empirically, results from 200 Vietnamese SMEs confirm that all three AI dimensions positively and significantly predict digital transformation, with Operational AI leading (β = 0.38), followed by Analytical AI (β = 0.27) and Customer-Facing AI (β = 0.19); together, the three dimensions explain 58% of digital transformation variance. Practically, the evidence-based ranking of AI effects provides SME managers with actionable investment sequencing guidance and equips policymakers with a contextual framework for designing targeted digitalization support.

Several limitations merit acknowledgment. The cross-sectional design precludes strong causal inference; longitudinal studies would better capture the temporal dynamics of AI-driven digital transformation. Additionally, the sample is confined to AI-adopting SMEs, which may introduce selection bias. Future research should explore the mediating roles of organizational capabilities, digital culture, and digital readiness in the AI-digital transformation relationship, and should test the model's generalizability across other ASEAN emerging economies.

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